SYNOPSIS REPORT ON

EARLY PREDICTION OF EPILEPSY USING THERMOGRAPHIC IMAGES AND AI APPROACH

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By

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August 2025

DECLARATION

I hereby declare that, the present work completed in the form of synopsis entitled, “Early Prediction of Epilepsy Using Thermographic Images and AI Approach” is an original work carried out by me under the guidance of Dr. Deepa Deshpande, and has not been submitted or published in any form for the fulfilment of any other degree or any other similar to this in other University.
I further declare that the material obtained from other sources has been duly acknowledged in the synopsis.

Pratima R Patil

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PLACE: CHHATRAPATI SAMBHAJINAGAR

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CERTIFICATE

This is to certify that Pratima Patil has carried out the work embodied in this synopsis entitled "**Early Prediction of Epilepsy Using Thermographic Images and AI Approach**". The work included in this synopsis is original, unless stated otherwise and has not been submitted for other degree of MGM University or any other University. References made to the work of others have been cited in the text.

SIGNATURE AND NAME OF RESEARCH SUPERVISOR

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Introduction

Febrile seizures (FSs) represent the most frequent type of seizures in children worldwide, with reported prevalence ranging between 2% and 11%. Although the majority of children experience only one seizure during a single febrile illness, recurrent febrile seizures (RFSs) occurring within 24 hours are observed in approximately 14–24% of cases [13]. Differentiating RFSs from other acute neurological conditions such as bacterial meningitis or severe encephalitis is clinically important, since these disorders can mimic FSs. However, significant central nervous system infections are rarely detected among children with RFS [14]. Repeated hospital admissions for such cases place a heavy emotional and financial burden on families and increase healthcare system costs. Therefore, identifying predictors of RFS is vital for prevention and for reducing both complications and medical expenses [16].

The likelihood of FS declines sharply after the age of four, and cases beyond seven years of age are exceedingly rare. According to the International League Against Epilepsy (ILAE), FSs are defined as seizures in infants or young children associated with fever $\geq 38^{\circ}$C, without evidence of central nervous system infection or acute metabolic disturbance [17]. Most FS episodes are benign, self-limiting, and rarely require long-term pharmacological treatment [20].

Genetic studies provide further insight into susceptibility, showing higher concordance rates among monozygotic twins compared to dizygotic twins [21]. Clinically, a febrile seizure may manifest as convulsions, loss of consciousness, or rhythmic movements, usually lasting a few minutes and resolving spontaneously [22]. Developing an individualized seizure management plan in collaboration with healthcare professionals ensures appropriate action in the event of recurrence, even though FSs typically do not result in permanent neurological damage [23].

FSs are classified as simple when they last less than 15 minutes and are associated with viral infections of the respiratory or gastrointestinal tract [24]. In contrast, seizures persisting for more than 30 minutes are termed febrile status epilepticus (FSE), which, although rare, accounts for 25–52% of childhood epilepsy cases [25]. Children who experience FSE are at greater risk of future recurrences, with up to 41% eventually developing additional FS episodes. Various risk factors for recurrence have been identified, including the child's age, sex, race, seizure characteristics, duration, neurodevelopmental abnormalities, and fever-related parameters such as peak temperature and duration before seizure onset [26]. Multivariate analyses further highlight that younger age, positive fam-

ily history, shorter fever duration, and lower body temperature significantly increase the likelihood of recurrence [27].

Despite these insights, limited research has explored the use of thermographic imaging in predicting recurrent FSs. Most existing studies rely heavily on electroencephalography (EEG) signals for diagnosis and prognosis. However, thermographic imaging offers a promising, non-invasive alternative for assessing physiological changes linked to FS recurrence. Challenges include the lack of large and diverse datasets, susceptibility of thermal readings to environmental noise, and difficulties in accurately capturing internal temperature variations. These limitations may reduce the robustness and generalizability of predictive models.

To address these challenges, this work proposes a novel deep learning–based framework for predicting recurrent febrile seizures using thermographic images. The main contributions are summarized as follows:

Novel predictive framework: A deep learning model specifically designed to estimate the likelihood of RFS from thermographic data.

Facial detection: Intra-Attentional Convolutional ResNet (InAtt-CRNet) integrated with the Yolov5-Face model for accurate localization of facial regions.

Temperature estimation: Forehead temperature measurement using an Enhanced Convolutional Capsule Network (EC2Net) with a Region of Interest (ROI)–based locating strategy.

Seizure recurrence prediction: Twin-directional Gated Long Short-Term Memory (TdG-LSTM) network applied to generate clinical decision rules and predict recurrence probability.

So to do early prediction it is mandatory to do survey of recent technology which is explained in next section.

Summary of Literature Survey and Research Gap

This Research Reviews the Literature on Machine Learning and Deep Learning techniques for epilepsy prediction attempts few Gap Analysis. To summarize the trends observed from literature, many studies used different deep learning techniques, but challenges like dataset shortage or early prediction of epilepsy remain common.

Research Gap

1. The input is always considered as EEG which will reduce accuracy.
2. The parameters considered to predict epilepsy disease to be modified.
3. Time required to predict must be reduced.
4. AI approach not used with thermo-graphic images
5. Only a few studies investigated thermal image-based seizure detection but not on human being.
6. No work is done on real time dataset.

Research Objectives and Scope

Objectives of Research

The primary objective of proposed method is to integrates advanced image processing with sophisticated machine-learning models to enhance the prediction of recurrent febrile seizures. By employing the MTIC-CNN model with Modified Trio-Net layers (P-Net, R-Net, and O-Net) and increased neuron density, the method achieves precise face detection and accurate temperature measurements:

1. To identify the effective methods for predicting epilepsy on early stages.
2. Survey from Medical Professionals and Patient on real time.
3. To predict the temperature that used to detect recurrent Febrile Seizure efficiently.
4. Alert patients their seizure is coming in the few months/hours.

Scope

1. Investigating current ML and neural network techniques for early prediction of epilepsy.
2. Designing and implementing a modified Trio-Net CNN model to achieve precise face detection and accurate temperature measurements from the nose or forehead.
3. Implementing Recurrent model effectively which captures temporal dependencies, providing accurate temperature predictions.
4. Analyzing performance vs. existing solutions for predicting and managing febrile seizure by increasing accuracy, adaptability, and scalability.

Contributions

Part 1 — Contribution-Model Development and Design

(i) Created unique dataset ETIC: The Epilepsy Thermal Imaging Cohort.

(ii) Identified the clinical gap in accurately predicting recurrent febrile seizures (RFS) using traditional methods.

(iii) Proposed an innovative hybrid model combining thermographic imaging and deep learning.

(iv) Integrated a Modified Trio-Net integrated Cascaded CNN (MTIC-CNN) for precise face and ROI (Region of Interest) detection.

(v) Incorporated Recurrent Elman Neural Network (RENN) for sequential temperature prediction.

(vi) Designed a XGBoost-based classifier to determine seizure risk from predicted temperature and clinical parameters.

Part 2 —Contribution-Technical Implementation

(i) Implemented the entire model pipeline using Python: including image preprocessing, face detection, temperature prediction, and seizure risk classification.

(ii) Derived and formulated critical mathematical expressions for convolution, pooling and XGBoost modeling.

(iii) Defined procedures to localize temperature-sensitive areas (nose and forehead) in thermal images.

(iv) Developed custom ROI equations for these regions to feed into the RENN.

Proposed Methodology and Results

Febrile seizures (FSs) are convulsions induced by fever, commonly affecting children between six months and five years of age. Recently, deep learning (DL) techniques have demonstrated considerable potential in analyzing medical imaging data for predictive healthcare applications. Despite this progress, few methods have been developed specifically for predicting recurrent FSs, and existing approaches often suffer from limitations such as low predictive accuracy, high computational costs, and overfitting. To address these challenges, a novel methodology has been proposed, aiming to enhance prediction accuracy while improving computational efficiency. The proposed methodology is divided into five parts as:

(i) Collection of Real Time Dataset: Collected Data of Total 35 Patients

(ii) Modified Trio-net Layers Integrated Cascaded CNN(MTIC-CNN) for detecting face from thermographic images.

(iii) ROI (Region of Interest) localization (nose/forehead).

(iv) Recurrent Elman Neural Network (RENN) for temperature prediction.

(v) Extreme Gradient Boosting (XGBoost) classifier for seizure risk prediction.

Part 1 — Collection of Real Time Dataset

Survey from Medical Professional Initially a retrospective review of medical records was conducted for patients aged 3 months to 10 years who had been hospitalized with febrile seizures (FS) at two training hospitals (Aundh hospital and Jagtap Clinic Pune). The study period was from January 2024 to September 2024. The primary goal of the study was to compare the clinical characteristics of patients with simple febrile seizures (SFS) to those with recurrent simple febrile seizures. To achieve this goal we required to gather data and information from different neurologist.The neurologist information table provides a comprehensive overview of several neurologists, detailing their specializations and specific suggestions they have provided.

Input Dataset. After discussion with medical professional and collecting history of patients we captured themographics images. Fig shows the thermographic image dataset.

Name of Neurologist	Specialization	Suggestion
Dr. Anand Soni (M.D.(Medicine) DM (Neurology))	Neurologist. Consultant Neuro Physical	Age Limit of Patient is Finalised
Dr. Umesh Kalane (MBBS DCH, DNB, MNAMS)	Fellowship in Paed. Neurology & Epilepsy, Fellow in Paediatric Neurology & Epilepsy, Fellow in Electroencephalographic (ADEPA) (ASNA), (IES)	Attribute Fever/ Non-Fever but at least one Episode
Dr. Sujit Jagtap (MD,DM)	Consultant Neurologist And Epileptologist and Movement disorder Specialist Neurology, Epilepsy, Sleep Disorder, Movement Disorder	1. Duration of Camera need to be finalised. 2. Use wearable camera

Table 1: Neurologist Information

Figure 1: The Epilepsy Thermal Imaging Cohort (ETIC)

Part 2 — Modified Trio-net Layers Integrated Cascaded CNN(MTIC-CNN) for detecting face from thermographic images.

The proposed system captures infrared face images from a thermal camera and performs detection and recognition in real time as shown in figure 5.2. The pipeline consists of

preprocessing, face detection (MTICCNN), landmark alignment, feature embedding, and matching. Thermal images require special handling: pixel values may need normalization and contrast enhancement [18]. For example, one approach is to scale raw thermal pixels to the 0–255 range and apply Contrast-Limited Adaptive Histogram Equalization (CLAHE) to highlight facial details [18] Some works even colorize or invert thermal images to better match the statistics of visible-light network [19]. The core detector is a modified MTIC-CNN. MTICCNN is a cascade of three CNNs (P-Net, R-Net, O-Net) that jointly regress face bounding boxes and five landmarks. To adapt it to thermal data, the single-channel infrared image can be replicated into three channels and pre-processed histogram-stretched so that existing RGB-trained models generalize better [19].

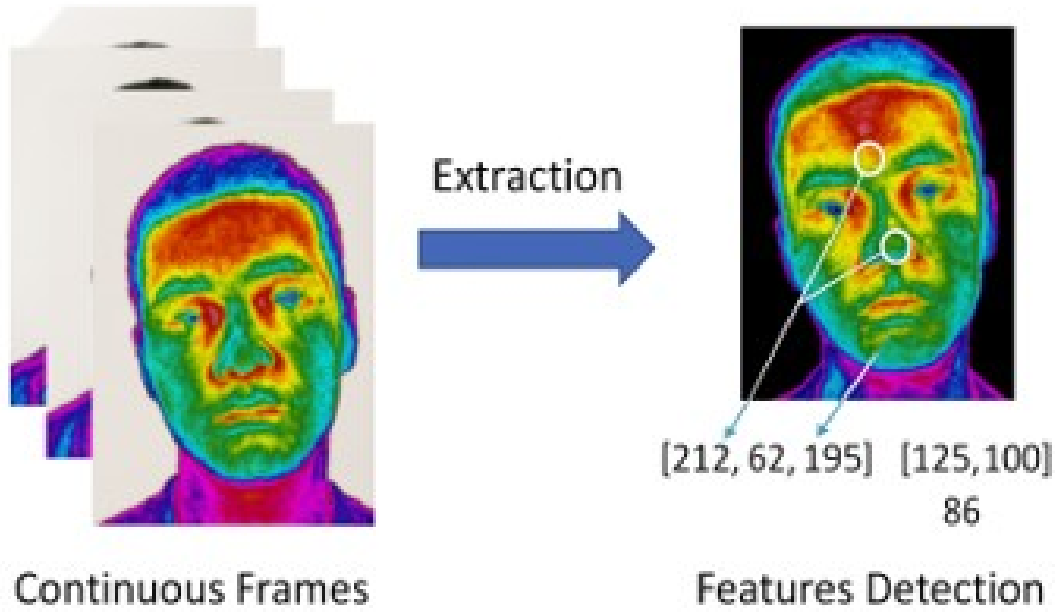

Figure 2: : Continuous images are required are captured in real time by camera and the featue matrix of keyframe face images is calculated by MTCNN algorithm

Part 3 — ROI (Region of Interest) localization (nose/forehead)

For subsequent measurement of body temperature, consider face facial features to define the forehead area as ROI as shown in Figure 5.3.

The ROI localization of nose is expressed as:

$$ROI_{Nose} = \sum_{u=A_x-\frac{B}{16}}^{A_x+\frac{B}{16}} \sum_{v=A_y-\frac{C}{16}}^{A_y+\frac{C}{16}} \mathrm{Im}\, g[u][v] \tag{1}$$

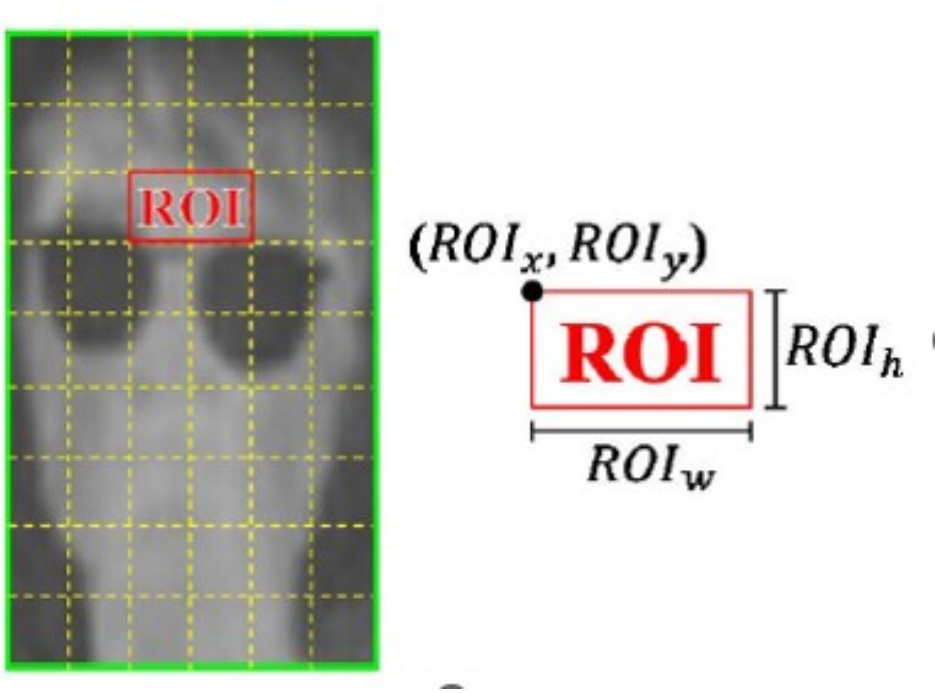

Figure 3: : Region of Interest

Then, the ROI localization of the forehead is:

$$ROI_{Fore-head} = \sum_{u=D_x-\frac{B}{12}}^{D_x+\frac{B}{12}} \sum_{v=A_y-\frac{C}{4}}^{A_y+\frac{C}{9}} \mathrm{Im}\, g[u][v] \tag{2}$$

Description of equation is mentioned below:

(i) In first equation Ax and Ay are nose coordinates.

(ii) Pixel values at the coordinates are defined as u,v .

(iii) Height and width are signified as C and B.

(iv) In second equation Dx,Dy represent the forehead coordinates.

Part 4 —Recurrent Elman Neural Network(RENN)

The input layer takes the input vector at each time step. Here, the input is the nose or forehead region localized by the MTIC-CNN model. The outcome of the input is fed into the hidden layer, which processes the input along with the context from the previous time step. The hidden layer in Elman networks is recurrent.Here, the context layer stores the previous hidden state, effectively serving as the memory component. The context is fed back into the hidden layer at the next time step. Finally, the output layer produces

the final output, which is the predicted temperature. The output layer is defined as:

$$O = \alpha \left(\sum_{q=1}^{p} V_{pq} b_q(t) \right) \tag{3}$$

The temperature obtained from the input thermographic image is the resulting output. It is then fed into the XGBoost algorithm to predict recurrent febrile seizures.

Part 5 —XGBoost based Recurrent Febrile Seizure Prediction

XGBoost is a gradient-boosted decision tree designed to enhance speed and performance. Its main characteristics include gradient boosting, an ensemble technique that adds new models to correct errors in existing models. XGBoost makes use of regularization, which helps to minimize overfitting and ensures reliable predictions, and parallel processing, which improves computing efficiency and speeds up training. The final prediction for a given data point is obtained by summing the outputs of all the trees in the model.

Results

The efficiency of the proposed technique is determined by comparing it with various existing techniques based on their performance such as Accuracy, precision, recall, and so on. The system configuration of the proposed technique is described in Table 6.1.

Table 2: System configuration

Processor	Intel(R) Core(TM) i5-9500 CPU @ 3.00 GHz 3.00 GHz
Installed RAM	16.0 GB (15.8 GB usable)
System type	64-bit operating system, x64-based processor
Pen and touch	There is no pen and touch is used

Dataset details

The thermographic images were gathered from various resources which include 500 thermographic images. In this research, an 80:20 ratio is considered to evaluate the performance of this model, here 80% of images are used to train the model, and 20% of images are used for testing. The sample images are represented in Figure 6.1.

Figure 4: : Sample images

Performance analysis

The Multiple performance indicators such as Accuracy, precision, recall, F1-score, specificity, MAE, MSE, and RMSE are represented in Figure 6.2.

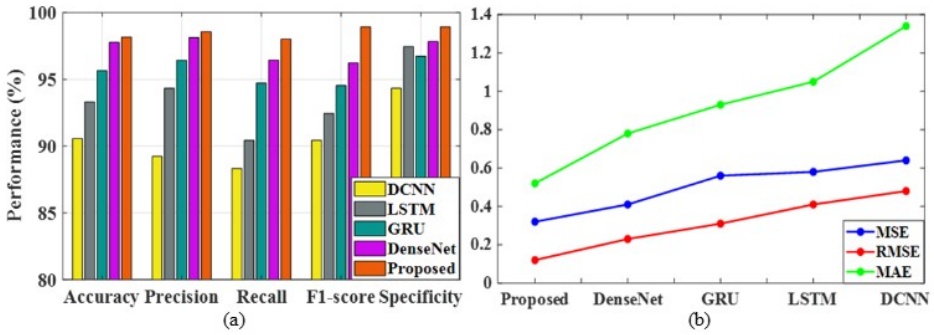

Figure 5: : Analysis of (a) Accuracy, Precision, Recall, F1-score, and Specificity, (b) MAE, MSE, and RMSE

Conclusion

The proposed framework combines advanced image processing with deep learning techniques to improve the prediction of recurrent febrile seizures. It employs an MTIC-CNN architecture enhanced with Modified Trio-Net components (P-Net, R-Net, and O-Net) and a higher neuron density, enabling accurate facial region detection and precise thermographic measurements from the nose and forehead. To capture temporal variations effectively, a Recurrent Neural Network (RENN) is utilized, ensuring reliable temperature prediction. These outputs, when integrated with clinical data through the XGBoost recursive model, contribute to improved evaluation metrics including accuracy, precision, recall, F1-score, specificity, and RMSE. Overall, the system demonstrates strong predictive capability compared to conventional approaches. However, its high computational demand may hinder real-time applications in low-resource settings. Future research should focus on optimizing the MTIC-CNN for reduced complexity and developing cost-efficient thermographic imaging techniques, making the approach more suitable for practical deployment.

Organisation of the Thesis

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List of Publications and Conference Attended

Publications

Journals

1. **Challenges and Issues in Detection of Seizure in Early Stages using Artificial Intelligence Approach**
   June 2024
   Indexing: Scopus Q4: International Journal of Medical Engineering and Informatics (IJMEI), Inderscience, January 2025. ISSN: 1755-0653
   Status: Accepted

2. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and Deep Learning**
   August 2024
   Indexing: Scopus Q1 : (BSPC-D-24-06842), under review at Biomedical Signal Processing and Control. ISSN: 1746-8094/8108
   Status: Accepted

3. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and AI Approach**
   December 2024
   Indexing: Scopus Q3 : (JCN-2024-12-0034), under review at Journal of Child Neurology
   Status: Under Review

Conferences

1. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and Deep Learning with Rules Generation**
   January 2025
   Indexing: 2025 1st International Conference on AIML-Applications for Engineering & Technology (ICAET), Pune, India. Jan 16-17, 2025
   Status: Published

2. **Twin-directional Gated Long Short-term Memory for Recurrent Febrile Seizure Prediction**
   June 2025
   Indexing: Scopus (Publisher: CRC Press Taylor & Francis Group)
   Status: Published

3. **Multi-task Cascaded Convolutional Neural Networks for Thermal Face Detection**
   May 2025
   Indexing: ISBM: The World Conference on Information Systems for Business Management, September 24, 2025, Bangkok
   Status: Accepted

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1. **Epthim: Unique Dataset For Epilepsy Thermal Image**
   January 2025
   Registration Number: 848/2025-CO/L
   Status: Under Review

2. **ETIC: The Epilepsy Thermal Imaging Cohort**
   April 2025
   Registration Number: LD-20731/2025-CO
   Status: Under Review

Introduction

Febrile seizures (FSs) represent the most frequent type of seizures in children worldwide, with reported prevalence ranging between 2% and 11%. Although the majority of children experience only one seizure during a single febrile illness, recurrent febrile seizures (RFSs) occurring within 24 hours are observed in approximately 14–24% of cases [13]. Differentiating RFSs from other acute neurological conditions such as bacterial meningitis or severe encephalitis is clinically important, since these disorders can mimic FSs. However, significant central nervous system infections are rarely detected among children with RFS [14]. Repeated hospital admissions for such cases place a heavy emotional and financial burden on families and increase healthcare system costs. Therefore, identifying predictors of RFS is vital for prevention and for reducing both complications and medical expenses [16].

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FSs are classified as simple when they last less than 15 minutes and are associated with viral infections of the respiratory or gastrointestinal tract [24]. In contrast, seizures persisting for more than 30 minutes are termed febrile status epilepticus (FSE), which, although rare, accounts for 25–52% of childhood epilepsy cases [25]. Children who experience FSE are at greater risk of future recurrences, with up to 41% eventually developing additional FS episodes. Various risk factors for recurrence have been identified, including the child's age, sex, race, seizure characteristics, duration, neurodevelopmental abnormalities, and fever-related parameters such as peak temperature and duration before seizure onset [26]. Multivariate analyses further highlight that younger age, positive family history, shorter fever duration, and lower body temperature significantly increase

the likelihood of recurrence [27].

Despite these insights, limited research has explored the use of thermographic imaging in predicting recurrent FSs. Most existing studies rely heavily on electroencephalography (EEG) signals for diagnosis and prognosis. However, thermographic imaging offers a promising, non-invasive alternative for assessing physiological changes linked to FS recurrence. Challenges include the lack of large and diverse datasets, susceptibility of thermal readings to environmental noise, and difficulties in accurately capturing internal temperature variations. These limitations may reduce the robustness and generalizability of predictive models.

To address these challenges, this work proposes a novel deep learning–based framework for predicting recurrent febrile seizures using thermographic images. The main contributions are summarized as follows:

Novel predictive framework: A deep learning model specifically designed to estimate the likelihood of RFS from thermographic data.

Facial detection: Intra-Attentional Convolutional ResNet (InAtt-CRNet) integrated with the Yolov5-Face model for accurate localization of facial regions.

Temperature estimation: Forehead temperature measurement using an Enhanced Convolutional Capsule Network (EC2Net) with a Region of Interest (ROI)–based locating strategy.

Seizure recurrence prediction: Twin-directional Gated Long Short-Term Memory (TdG-LSTM) network applied to generate clinical decision rules and predict recurrence probability.

So to do early prediction it is mandatory to do survey of recent technology which is explained in next section.

Summary of Literature Survey and Research Gap

This Research Reviews the Literature on Machine Learning and Deep Learning techniques for epilepsy prediction attempts few Gap Analysis. To summarize the trends observed from literature, many studies used different deep learning techniques, but challenges like dataset shortage or early prediction of epilepsy remain common.

Research Gap

1. The input is always considered as EEG which will reduce accuracy.
2. The parameters considered to predict epilepsy disease to be modified.
3. Time required to predict must be reduced.
4. AI approach not used with thermo-graphic images
5. Only a few studies investigated thermal image-based seizure detection but not on human being.
6. No work is done on real time dataset.

Research Objectives and Scope

Objectives of Research

The primary objective of proposed method is to integrates advanced image processing with sophisticated machine-learning models to enhance the prediction of recurrent febrile seizures. By employing the MTIC-CNN model with Modified Trio-Net layers (P-Net, R-Net, and O-Net) and increased neuron density, the method achieves precise face detection and accurate temperature measurements:

1. To identify the effective methods for predicting epilepsy on early stages.
2. Survey from Medical Professionals and Patient on real time.
3. To predict the temperature that used to detect recurrent Febrile Seizure efficiently.
4. Alert patients their seizure is coming in the few months/hours.

Scope

1. Investigating current ML and neural network techniques for early prediction of epilepsy.
2. Designing and implementing a modified Trio-Net CNN model to achieve precise face detection and accurate temperature measurements from the nose or forehead.
3. Implementing Recurrent model effectively which captures temporal dependencies, providing accurate temperature predictions.
4. Analyzing performance vs. existing solutions for predicting and managing febrile seizure by increasing accuracy, adaptability, and scalability.

Contributions

Part 1 — Contribution-Model Development and Design

(i) Created unique dataset ETIC: The Epilepsy Thermal Imaging Cohort.

(ii) Identified the clinical gap in accurately predicting recurrent febrile seizures (RFS) using traditional methods.

(iii) Proposed an innovative hybrid model combining thermographic imaging and deep learning.

(iv) Integrated a Modified Trio-Net integrated Cascaded CNN (MTIC-CNN) for precise face and ROI (Region of Interest) detection.

(v) Incorporated Recurrent Elman Neural Network (RENN) for sequential temperature prediction.

(vi) Designed a XGBoost-based classifier to determine seizure risk from predicted temperature and clinical parameters.

Part 2 —Contribution-Technical Implementation

(i) Implemented the entire model pipeline using Python: including image preprocessing, face detection, temperature prediction, and seizure risk classification.

(ii) Derived and formulated critical mathematical expressions for convolution, pooling and XGBoost modeling.

(iii) Defined procedures to localize temperature-sensitive areas (nose and forehead) in thermal images.

(iv) Developed custom ROI equations for these regions to feed into the RENN.

Proposed Methodology and Results

Febrile seizures (FSs) are convulsions induced by fever, commonly affecting children between six months and five years of age. Recently, deep learning (DL) techniques have demonstrated considerable potential in analyzing medical imaging data for predictive healthcare applications. Despite this progress, few methods have been developed specifically for predicting recurrent FSs, and existing approaches often suffer from limitations such as low predictive accuracy, high computational costs, and overfitting. To address these challenges, a novel methodology has been proposed, aiming to enhance prediction accuracy while improving computational efficiency. The proposed methodology is divided into five parts as:

(i) Collection of Real Time Dataset: Collected Data of Total 35 Patients

(ii) Modified Trio-net Layers Integrated Cascaded CNN(MTIC-CNN) for detecting face from thermographic images.

(iii) ROI (Region of Interest) localization (nose/forehead).

(iv) Recurrent Elman Neural Network (RENN) for temperature prediction.

(v) Extreme Gradient Boosting (XGBoost) classifier for seizure risk prediction.

Part 1 — Collection of Real Time Dataset

Survey from Medical Professional Initially a retrospective review of medical records was conducted for patients aged 3 months to 10 years who had been hospitalized with febrile seizures (FS) at two training hospitals (Aundh hospital and Jagtap Clinic Pune). The study period was from January 2024 to September 2024. The primary goal of the study was to compare the clinical characteristics of patients with simple febrile seizures (SFS) to those with recurrent simple febrile seizures. To achieve this goal we required to gather data and information from different neurologist.The neurologist information table provides a comprehensive overview of several neurologists, detailing their specializations and specific suggestions they have provided.

Input Dataset. After discussion with medical professional and collecting history of patients we captured themographics images. Fig shows the thermographic image dataset.

Name of Neurologist	Specialization	Suggestion
Dr. Anand Soni (M.D.(Medicine) DM (Neurology))	Neurologist. Consultant Neuro Physical	Age Limit of Patient is Finalised
Dr. Umesh Kalane (MBBS DCH, DNB, MNAMS)	Fellowship in Paed. Neurology & Epilepsy, Fellow in Paediatric Neurology & Epilepsy, Fellow in Electroencephalographic (ADEPA) (ASNA), (IES)	Attribute Fever/ Non-Fever but at least one Episode
Dr. Sujit Jagtap (MD,DM)	Consultant Neurologist And Epileptologist and Movement disorder Specialist Neurology, Epilepsy, Sleep Disorder, Movement Disorder	1. Duration of Camera need to be finalised. 2. Use wearable camera

Table 1: Neurologist Information

Figure 1: The Epilepsy Thermal Imaging Cohort (ETIC)

Part 2 — Modified Trio-net Layers Integrated Cascaded CNN(MTIC-CNN) for detecting face from thermographic images.

The proposed system captures infrared face images from a thermal camera and performs detection and recognition in real time as shown in figure 5.2. The pipeline consists of preprocessing, face

detection (MTICCNN), landmark alignment, feature embedding, and matching. Thermal images require special handling: pixel values may need normalization and contrast enhancement [18]. For example, one approach is to scale raw thermal pixels to the 0–255 range and apply Contrast-Limited Adaptive Histogram Equalization (CLAHE) to highlight facial details [18] Some works even colorize or invert thermal images to better match the statistics of visible-light network [19]. The core detector is a modified MTIC-CNN. MTICCNN is a cascade of three CNNs (P-Net, R-Net, O-Net) that jointly regress face bounding boxes and five landmarks. To adapt it to thermal data, the single-channel infrared image can be replicated into three channels and pre-processed histogram-stretched so that existing RGB-trained models generalize better [19].

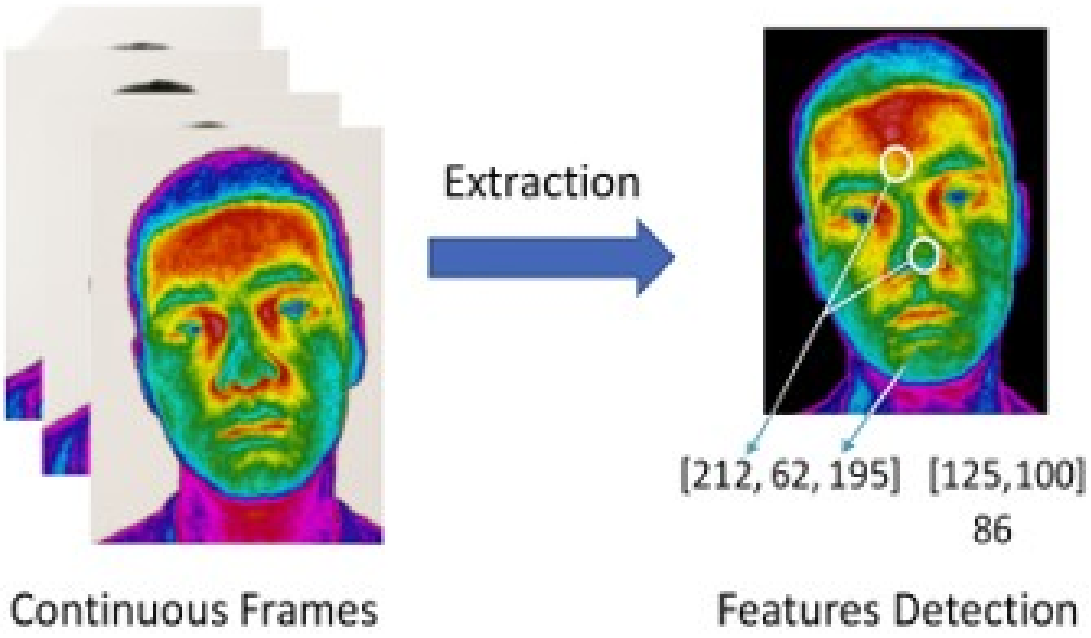

Figure 2: : Continuous images are required are captured in real time by camera and the featue matrix of keyframe face images is calculated by MTCNN algorithm

Part 3 — ROI (Region of Interest) localization (nose/forehead).

For subsequent measurement of body temperature, consider face facial features to define the forehead area as ROI as shown in Figure 5.3.

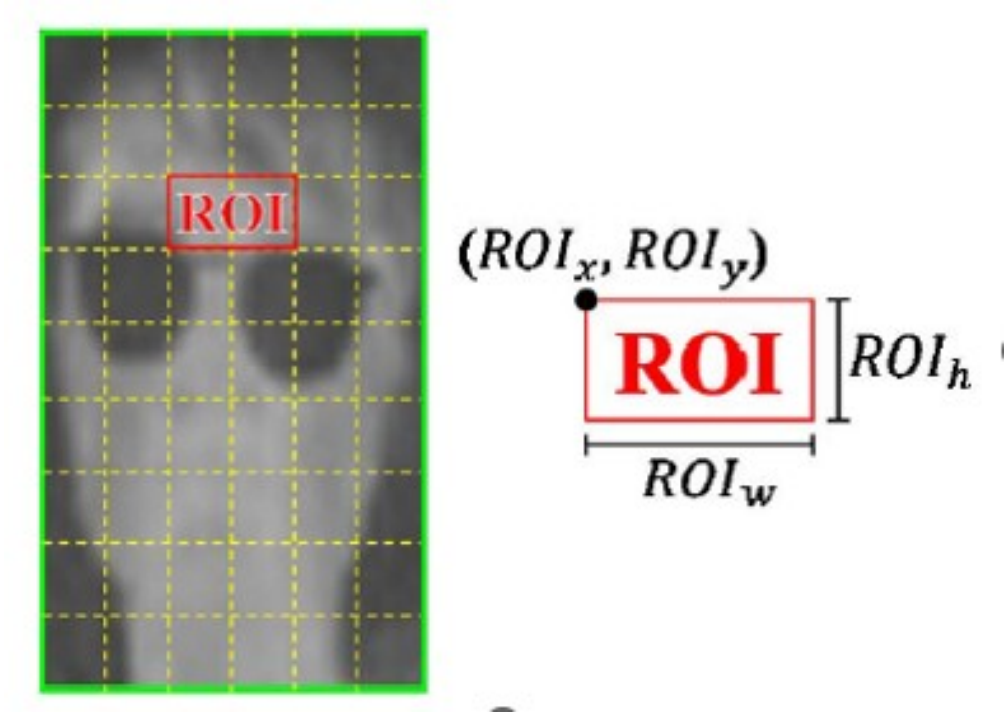

Figure 3: : Region of Interest

The ROI localization of nose is expressed as:

$$ROI_{Nose} = \sum_{u=A_x-\frac{B}{16}}^{A_x+\frac{B}{16}} \sum_{v=A_y-\frac{C}{16}}^{A_y+\frac{C}{16}} \mathrm{Im}\, g[u][v] \tag{1}$$

Then, the ROI localization of the forehead is:

$$ROI_{Fore-head} = \sum_{u=D_x-\frac{B}{12}}^{D_x+\frac{B}{12}} \sum_{v=A_y-\frac{C}{4}}^{A_y+\frac{C}{9}} \mathrm{Im}\, g[u][v] \tag{2}$$

Description of equation is mentioned below:

(i) In first equation Ax and Ay are nose coordinates.

(ii) Pixel values at the coordinates are defined as u,v .

(iii) Height and width are signified as C and B.

(iv) In second equation Dx,Dy represent the forehead coordinates.

Part 4 —Recurrent Elman Neural Network(RENN)

The input layer takes the input vector at each time step. Here, the input is the nose or forehead region localized by the MTIC-CNN model. The outcome of the input is fed into the hidden layer, which processes the input along with the context from the previous time step. The hidden layer in Elman networks is recurrent.Here, the context layer stores the previous hidden state, effectively serving as the memory component. The context is fed back into the hidden layer at the next time step. Finally, the output layer produces the final output, which is the predicted temperature. The output layer is defined as:

$$O = \alpha \left(\sum_{q=1}^{p} V_{pq} b_q(t) \right) \tag{3}$$

The temperature obtained from the input thermographic image is the resulting output. It is then fed into the XGBoost algorithm to predict recurrent febrile seizures.

Part 5 —XGBoost based Recurrent Febrile Seizure Prediction

XGBoost is a gradient-boosted decision tree designed to enhance speed and performance. Its main characteristics include gradient boosting, an ensemble technique that adds new models to correct errors in existing models. XGBoost makes use of regularization, which helps to minimize overfitting and ensures reliable predictions, and parallel processing, which improves computing efficiency and speeds up training. The final prediction for a given data point is obtained by summing the outputs of all the trees in the model.

Results

The efficiency of the proposed technique is determined by comparing it with various existing techniques based on their performance such as Accuracy, precision, recall, and so on. The system configuration of the proposed technique is described in Table 6.1.

Table 2: System configuration

Processor	Intel(R) Core(TM) i5-9500 CPU @ 3.00 GHz 3.00 GHz
Installed RAM	16.0 GB (15.8 GB usable)
System type	64-bit operating system, x64-based processor
Pen and touch	There is no pen and touch is used

Figure 4: : Sample images

Dataset details

The thermographic images were gathered from various resources which include 500 thermographic images. In this research, an 80:20 ratio is considered to evaluate the performance of this model, here 80% of images are used to train the model, and 20% of images are used for testing. The sample images are represented in Figure 6.1.

Performance analysis

The Multiple performance indicators such as Accuracy, precision, recall, F1-score, specificity, MAE, MSE, and RMSE are represented in Figure 6.2.

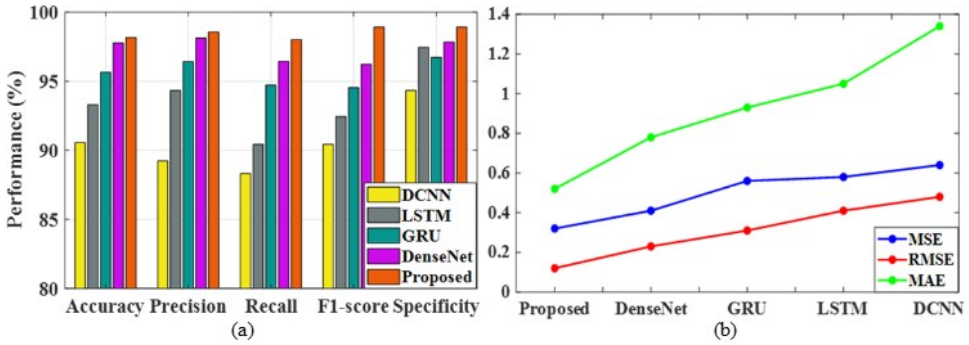

Figure 5: : Analysis of (a) Accuracy, Precision, Recall, F1-score, and Specificity, (b) MAE, MSE, and RMSE

Conclusion

The proposed framework combines advanced image processing with deep learning techniques to improve the prediction of recurrent febrile seizures. It employs an MTIC-CNN architecture enhanced with Modified Trio-Net components (P-Net, R-Net, and O-Net) and a higher neuron density, enabling accurate facial region detection and precise thermographic measurements from the nose and forehead. To capture temporal variations effectively, a Recurrent Neural Network (RENN) is utilized, ensuring reliable temperature prediction. These outputs, when integrated with clinical data through the XGBoost recursive model, contribute to improved evaluation metrics including accuracy, precision, recall, F1-score, specificity, and RMSE. Overall, the system demonstrates strong predictive capability compared to conventional approaches. However, its high computational demand may hinder real-time applications in low-resource settings. Future research should focus on optimizing the MTIC-CNN for reduced complexity and developing cost-efficient thermographic imaging techniques, making the approach more suitable for practical deployment.

Organisation of the Thesis

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List of Publications and Conference Attended

Publications

Journals

1. **Challenges and Issues in Detection of Seizure in Early Stages using Artificial Intelligence Approach**
   June 2024
   Indexing: Scopus Q4: International Journal of Medical Engineering and Informatics (IJMEI), Inderscience, January 2025. ISSN: 1755-0653
   Status: Accepted

2. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and Deep Learning**
   August 2024
   Indexing: Scopus Q2 : (BSPC-D-24-06842), under review at Biomedical Signal Processing and Control. ISSN: 1746-8094/8108
   Status: Accepted

3. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and AI Approach**
   December 2024
   Indexing: Scopus Q3 : (JCN-2024-12-0034), under review at Journal of Child Neurology
   Status: Under Review

Conferences

1. **Predicting the Likelihood of a Recurrent Febrile Seizure Using Thermographic Images and Deep Learning with Rules Generation**
   January 2025

Indexing: 2025 1st International Conference on AIML-Applications for Engineering & Technology (ICAET), Pune, India. Jan 16-17, 2025
Status: Published

2. **Twin-directional Gated Long Short-term Memory for Recurrent Febrile Seizure Prediction**
June 2025
Indexing: Scopus (Publisher: CRC Press Taylor & Francis Group)
Status: Published

3. **Multi-task Cascaded Convolutional Neural Networks for Thermal Face Detection**
May 2025
Indexing: ISBM: The World Conference on Information Systems for Business Management, September 24, 2025, Bangkok
Status: Accepted

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1. **Epthim: Unique Dataset For Epilepsy Thermal Image**
January 2025
Registration Number: 848/2025-CO/L
Status: Under Review

2. **ETIC: The Epilepsy Thermal Imaging Cohort**
April 2025
Registration Number: LD-20731/2025-CO
Status: Under Review